Effects of a Minimum Wage Increase on Restaurants: Price Pass-Through, Quality Changes, and Border Effects

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Abstract

The stagnant federal minimum wage in the U.S. has spurred an unprecedented number of state, county, and citywide minimum wage laws. The high number and varying magnitudes of minimum wage increases combined with the growing online presence of restaurants provides a unique setting in which to analyze the effects of a minimum wage increase on restaurants' prices and quality. Using a novel dataset comprised of menu item and restaurant quality information from thousands of East Coast establishments across three states, I estimate the effects of varying levels of minimum wage increases enacted at the start of 2017. I find that prices rise 0.3% to 1.1% in response to a 10% increase in the minimum wage. These price pass-through effects are heterogeneous across restaurant characteristics and item type. Further, the magnitude of price pass-through is lower for restaurants near the border of a minimum wage policy region, suggesting that local minimum wage policies may negatively affect businesses on the border. Finally, I find that customer-perceived quality of restaurants is positively related to increases in the minimum wage for restaurants with high rating levels prior to a minimum wage hike, but negatively related for restaurants with low rating levels.

JEL Classifications: J08, J30, H70

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1 Introduction

The federal minimum wage in the United States has remained stagnant for almost a decade at $7.25, which is over 30% lower in real terms than the federal minimum wage in 1970. As a result of this stagnation, a significant number of states, counties and cities across the country have introduced, or are considering introducing, a local minimum wage. In 2012 there were only five city or county minimum wage laws across the country, but by the beginning of 2017 there were over 40 (UC Berkely Center for Labor Research and Education, 2016). The number of state level minimum wage laws has also increased, with 19 states raising their respective minimum wage at the beginning of 2017 (The Economic Policy Institute, 2017). Despite the prevalence of such policies, there remains no clear consensus in the minimum wage literature about the total effects of a minimum wage increase. The unique nature of the datasets, based on restaurant menus, that I use in this paper allow for more extensive analysis of minimum wage related questions. These additional areas of study include heterogeneity in price pass-through across restaurant characteristics and item type, changes in restaurant quality, and the difference in pass-through for restaurants closer to the border of a minimum wage policy region.

Nearly three-fifths of all workers paid at or below the minimum wage are employed in the service industry (U.S. Bureau of Labor Statistics, 2016), making restaurants an ideal sector in which to analyze the effects of a minimum wage increase on price and quality. The price of restaurant food has become an integral part of the American budget. In 2015, for the first time in history, Americans spent more money eating out at restaurants than they did on groceries (United States Department of Agriculture, 2017). Price changes due to a minimum wage increase also have implications about the underlying employment structure of the restaurant industry. Card and Kruger (1994) found a small positive effect on employment and no effect on prices after an increase in the minimum wage. These findings contradicted the textbook model of competitive labor markets, a model which predicts an increase in output prices and a decrease in employment. In response to Card and Kruger (1994), many studies analyzed the existence of monopsony power in the labor market (e.g. Manning (1995); Rebitzer & Taylor (1995); Burdett & Mortensen (1998); Bhaskar & To (1999)), as a monopsony model predicts an increase in employment and a decrease in prices. Neumark and Wascher (2006) conclude in their survey of the literature that the most rigorous and reliable studies have found significant price increases and small employment decreases. As Aaronson, French and MacDonald (2008) conclude, the presence of significant increases in price in response to minimum wage increases is evidence against the prevalence of monopsony power in the labor market.

In the literature, the magnitude of the price pass-through to consumers after a 10% increase in minimum wage varies between 0.4% and 1.5%. The following are specific examples that are most closely related to this paper. Allegrotto and Reich (2015) use full online menus to analyze prices before and after a local minimum wage increase in San Jose, and find pass-through to be 0.58%. Aaronsen, French and MacDonald (2008) utilize the store level data that comprises the food away from home component of the Consumer Price Index. This data contains several bundles of food, usually the equivalent of a meal, at a variety of establishments across the country. Using variation in state and federal minimum wage changes, the authors estimate a price pass-through of 0.7%. Basker and Khan (2013) estimate a price pass-through of 0.9% for McDonald's Quarter Pounders and Pizza Hut's regular cheese pizzas using state level variation in the minimum wage. These estimates vary with the types of items and time period analyzed but show that restaurants consistently pass-through the increased labor costs in the form of higher output prices.

In this paper, I examine restaurants in New York, Massachusetts, and New Jersey. These three contiguous states on the East Coast increased their respective minimum wages on the first day of 2017, with four different levels of increase within the state of New York. I examine the impact of the minimum wage changes using restaurant menus from Yelp.com and Grubhub.com. Using these datasets, I estimate the overall price pass-through at the restaurant level due to a 10% increase in minimum wage to be between 0.3% and 1.1%, depending on the subsample analyzed. These estimates are consistent with previous findings in the literature as discussed above. Unlike traditional administrative or government datasets, the data used in this study provide granular restaurant and menu data at the item level. Furthermore, these data provide additional variables of interest, such as measures of quality, that are not available in traditional datasets. Utilizing restaurant specific characteristics, I find that the magnitude of the price pass-through estimate is heterogeneous across restaurant characteristics, with small restaurants showing higher pass-through at over 0.7%. The magnitude of the price pass-through also varies at the item level, where popular items, side items, and sandwiches show a pass-through level of over 0.6%, but drinks and entrés show significantly lower levels of pass-through, with estimates below 0.4%. This suggests that studies which examine prices of only a few menu items may significantly over or under estimate overall price pass-through.

In addition to prices, restaurant quality could also change as a result of a minimum wage increase. For example, decreases in overall restaurant quality after a minimum wage hike could come in the form of reduced portion sizes or decreased quality of ingredients. On the other hand, an increase in the minimum wage could improve service quality by acting as an efficiency wage. Restaurants could also substitute toward more productive workers by decreasing work hours for less productive employees, improving average service quality. This is the first paper to analyze changes in customer-perceived quality due to a change in minimum wage. Using the consumer rated star values from the Yelp review platform, I estimate the impact of a 10% minimum wage increase on the customer rating of restaurants, finding a bimodal effect. Restaurants that were rated at the median (3.5) or below prior to the minimum wage increase saw a significant decrease in the star rating given to them by consumers, a decrease of more than 1%. Restaurants that started at ratings above 3.5 stars saw a positive effect on their consumer ratings due to the increase in minimum wage, an increase of approximately 0.3%. These results suggest that firms may react to a minimum wage increase differently depending on initial quality. A similar conclusion was drawn by Luca and Luca (2017), who used Yelp data to analyze the probability of restaurant closure after a minimum wage increase. The authors found that the likelihood of exit after a minimum wage hike was negatively related to initial restaurant quality. To investigate potential mechanisms of these overall quality effects found in the Yelp data, I next analyze changes in the Grubhub food specific quality measure. I find that for restaurants starting at or below the median food quality rating, minimum wage is negatively related to changes in food quality, but positively related for restaurants starting above the median rating. These food specific quality results support the overall quality results found in the Yelp data and provide support for the potential underlying mechanisms of these quality changes due to a minimum wage increase.

One potential negative effect of a minimum wage increase is the inability of restaurants close to the border of the city, county, or state to account for these increased input costs in the form of higher prices without losing business. Restaurants facing minimum wage increases close to a border where restaurants on the opposite side of the border are not facing an increase in labor costs may keep prices lower in order to compete. These effects are referred to as border effects, and can be measured by the existence of a relationship between the distance a restaurant is to a bordering area with a different minimum wage increase and the magnitude of the price increase. The existence of border effects is crucial with regard to policy evaluation and fully understanding how local businesses are affected by changes in minimum wage policy. This paper provides the most comprehensive analysis on the existence of border effects to date in the literature. For restaurants located close to a bordering area that is facing a lower minimum wage hike, I find a significant relationship between a restaurant's proximity to the border and the level of price pass-through. Specifically, I estimate that a restaurant ten minutes farther away from the border increases prices by 0.2 percentage points more than a restaurant on the border. These restaurants that are on the border do not increase prices by more than the restaurants on the opposite side of the border. These border effects suggest that a local minimum wage increase may impede the ability of restaurants to fully pass-through prices to consumers due to the spatial proximity to competitors who are not facing an increase in minimum wage.

2 Minimum Wage Laws

On January 1, 2017, three contiguous states on the East Coast - Massachusetts, New Jersey, and New York - increased their minimum wage at differing magnitudes, with a variety of levels of increase within the state of New York. Table I reports the increases in minimum wage in these areas, which range from 0.72% to 22.22%. These states provide a useful setting for minimum wage analysis as they are in the same geographic region and have similar economic, demographic, and political characteristics. Each area faced the changes in minimum wage over the same time period.

In April of 2016, New York (NY) became the second state, after California, to pass a law that would incrementally raise the minimum wage for all workers to $15/hour.[1] In this law, which applies to all non-fast food restaurants, the degree of the minimum wage increase is based on the type and location of the establishment (2015-2016 New York Legislative Session, 2016). The first two rows of Table I report minimum wage changes for restaurants in New York City (NYC). Restaurants in NYC with more than ten employees, denoted as large restaurants, saw a 22.22% increase, from $9 to $11 per hour. Small restaurants in NYC saw an increase of 16.67%, from $9 to $10.50. The third column of Table I includes restaurants of all sizes in the three contiguous counties outside of NYC: Nassau, Suffolk, and Westchester. These three counties are referred to throughout this paper as NYC MSA. These restaurants saw an 11.11% increase, from $9 to $10. The final NY group, NY Upstate, which includes restaurants of all sizes elsewhere in the state of NY, saw a 7.78% increase, from $9 to $9.70.

Two states contiguous to NY saw changes in their own state-wide minimum wage laws on January 1, 2017. Massachusetts (MA) passed a bill in 2014 that increased the minimum wage by $1 a year from 2015 to 2017. This bill increased the minimum wage on January 1, 2017 by 10.00%, from $10 to $11. (State of Massachusetts General Assembly, 2014). In the spring of 2016, New Jersey (NJ) proposed a minimum wage

[1] In 2015, NY passed a minimum wage law only applicable to fast food restaurants, increasing the minimum wage each year for fast food workers (New York State Department of Labor, 2015). Due to the small sample size and unique nature of fast food restaurants in the data, I exclude all fast food restaurants from the analysis.

law similar to that of NY that would have raised the minimum wage to $10.10 per hour on January 1, 2017, and would incrementally raise the minimum wage until the state reached $15/hour (State of New Jersey Senate Budget and Appropriations Committee, 2016). The bill passed through the House and the Senate, but in August of 2016, NJ governor Chris Christie vetoed the bill, stating "...[this bill] fails to consider the capacity of businesses, especially small businesses, to absorb the substantially increased labor costs it will impose"(Christie, 2016). Thus, in 2017, NJ increased the state minimum wage by only 0.72%, a yearly adjustment for inflation (State of New Jersey Department of Labor and Workforce Development, 2014). The state of NJ is therefore a strong counterfactual to NY and MA because of the state's similar legislative intent but divergent application due to Christie's veto.

3 Data

I use three primary datasets to understand the impact of increases in the minimum wage on restaurants' prices and quality. The first, and most extensive, is a panel dataset comprised of restaurant menu and quality information from Yelp.com. The second is a supplementary panel dataset comprised of restaurant menu information from Grubhub.com. The third is a dataset providing detailed restaurant business information from ReferenceUSA. I utilize these datasets to determine the magnitude of price pass-through to consumers, how this pass-through varies by restaurant and item specific characteristics, and how the minimum wage impacted customer-perceived quality.

3.1 Yelp

Yelp.com is a website in which consumers can find restaurant information including customer reviews, hours of operation, price range, and full menus. Yelp was founded in 2004, and currently has an average of 72 million monthly visitors with over 115 million reviews written (*An Introduction to Yelp Metrics*, 2016). Using a web scrape, I conducted the first wave of Yelp data collection in April 2016, the second wave in July 2016, and the third wave in October 2016. Two waves of data collection occurred after the minimum wage increases, in January 2017 and April 2017.[2] I collected information from the Yelp homepage of 69,224 restaurants within NY, NJ, and MA. Of these, 21,688, or approximately one third of these restaurants,

[2] See the Appendix for further details about the data collection process.

provide a full menu on Yelp.[3] In a similar study using online menus, Allegrotto and Reich (2015) also found that, on average, about one third of restaurants posted full online menus. Some Yelp restaurants, primarily chain restaurants, provide a full menu but do not include location specific prices. Out of the restaurants that post full menus, 17,385 of them include location specific prices. To match each restaurant to a minimum wage group, 15,087 restaurants were matched by address to a county using the Census Geocoder. The 47 fast food restaurants were removed from the dataset. To create a balanced panel, the final sample used in the analysis contains the 8,805 restaurants that posted location specific prices in all waves of data collection. Reasons that restaurants fail to be in all waves of data collection include closures, name changes, or discontinued use of a Yelp menu.

Yelp users provide online reviews of restaurants and assign them an overall star rating on a scale of 1 to 5, with 1 representing extremely poor and 5 representing outstanding. Although the number of stars that a restaurant has earned is determined by self-selected reviewers, the Yelp star rating has been found to be a reliable predictor of actual quality as well as an important determinant of profit for restaurants. In a study comparing Yelp star ratings of hospitals to an industry standard assessment of quality, Bardach *et al.* (2014) found that Yelp stars were significantly related to patient care and health outcomes. Luca (2011) used a regression-discontinuity design to analyze the impact of a change in the Yelp star rating on restaurants, and found that a one-star increase in the Yelp rating led to a 5-9% increase in revenue. A concern of using Yelp stars as a point of analysis regards the potential of restaurants writing fake reviews – both good reviews of themselves and bad reviews of competitors. Yelp uses a proprietary algorithm in an attempt to filter out fake reviews, which are not included in the overall Yelp star rating. Although some fake reviews may still exist, it is unlikely that any fake reviews on quality are correlated with changes in the minimum wage. The rounded star rating that customers see prominently displayed on each restaurant's homepage is the monthly average of all Yelp reviews rounded to the nearest half star.[4] There is significant variation in the Yelp star rating for restaurants over the time period of the dataset, an indication that Yelp users are active in reporting the current quality of the establishments. Over 50 percent of restaurants see a change in star rating between any given observation period, and the average change given an increase (decrease) is 0.62 (0.61) stars.

[3] Some restaurants provide an external link to a menu, but since these menus are not formatted uniformly, the menu information cannot be correctly parsed and thus, for the sake of this dataset, these restaurants fall into the same category as those restaurants who do not provide an online menu. These externally formatted menus were hand entered for one round of the scrape, and the average price of these restaurants was not statistically different from the Yelp formatted menus. See the Appendix for the comparison table reporting all characteristics.

[4] If a restaurant has less than 10 reviews within a month, then the most recent reviews are added until the sample size reaches 10.

3.2 Grubhub

Founded in 2004, Grubhub.com is the largest online food ordering company in the U.S., providing its 7.7 million customers in over 1,100 cities access to delivery at over 45,000 locations (*Grubhub, About Us*, 2016). I collected the Grubhub data with the primary intention of validating the main Yelp data. I collected menu information for all Grubhub restaurants in the areas of interest using a second webscrape in December 2016, January 2017, February 2017, March 2017 and April 2017. Although there are fewer restaurants on Grubhub than there are on Yelp, the Grubhub menu prices, which are necessarily up to date given the nature of the delivery service, provide an idea to what extent the Yelp data is generalizable. I collect menus for 12,217 restaurants. Of these, 10,414 were matched to a county using the Census Geocoder. After removing the 67 fast food restaurants, 7,280 restaurant comprise the final balanced panel. All restaurants on Grubhub provide a uniform menu and are therefore included in the dataset of parsed menu information. The food specific measure of quality that is used in the quality analysis is a rating from 0 to 100 that identifies the proportion of customers who reported that "the food was good" after receiving their food order.

3.3 ReferenceUSA

I utilize ReferenceUSA (RUSA), an Infogroup company that provides business data, to define more detailed characteristics of the restaurants. I collect the data for all businesses in NY, MA, and NJ that are categorized under the North American Industry Classification System (NAICS) as a full-service or limited-service restaurant. The restaurant level variables obtained from this dataset include sales volume, number of employees, limited service status, and franchise status. Since these data are updated on a yearly basis, the variables are used only as baseline characteristics of the establishments.

3.4 Data Construction and Definitions

To determine the minimum wage that the restaurants face, I match each restaurant to a county using the Census Geocoder. In NYC, the minimum wage that a non-fast-food restaurant faces is dependent on the number of employees. The RUSA dataset provides the number of employees at each location, however I am only able to match approximately half of the Yelp and Grubhub restaurants to the RUSA dataset. Therefore, in this study I use the average minimum wage increase in NYC, 19.45%, for restaurants of all size in NYC.[5] Since there are significantly more restaurants that qualify as "small" in NYC, using the un-weighted average of the minimum wage increase will only bias my estimates towards zero. Figure 1 displays the geographic distribution of the restaurants in the Yelp dataset.

For the Yelp and Grubhub menu data, I create a balanced panel at the item level, only including restaurants and items that are in all waves of data collection. One concern with using a balanced panel is that firms could respond to changes in the minimum wage by changing the items offered. However, I find no clear relationship between changes in the total number of items offered at a restaurant and changes in the minimum wage. Another concern is that firms may change the quality of the items in the balanced sample. These potential quality changes are addressed in Section 5. A third concern is that restaurants may close in response to a minimum wage increase (D. L. Luca & Luca, 2017). To address this, I estimate the price pass-through from October 2016 to January 2017 using all Yelp restaurants that remained in the panel through January 2017. I then estimate this same price pass-through using only the restaurants that remained in the panel through April 2017. I find the two estimates to be statistically indistinguishable, although including the restaurants that dropped out of the panel before April 2017 yielded slightly higher pass-through estimates. This suggests that only including restaurants that remain open for business throughout the time period of the dataset does not bias my results, and if anything would lead the results to be a lower bound of the true pass-through.

Summary statistics of the balanced panels aggregated at the restaurant level for Yelp and Grubhub are reported in Table II and Table III, respectively. In the Yelp dataset, changes in price from April 2016 to October 2016 are not statistically different in each of the minimum wage groups, providing support that the restaurants in NJ are a strong comparison group to NY and MA. The price changes over the time period of the minimum wage policy changes and the percent of price increases are significantly different between groups in both datasets. As shown in these tables, restaurants update menus less frequently in the Yelp dataset than the Grubhub dataset, but changes in price conditional on an increase or decrease in price are larger in the Yelp dataset. This is consistent with the properties of each web source. Yelp menus are updated at the owner or manager's discretion, and may not always provide updated prices. Grubhub, however, provides

[5] I match on address, phone number, and restaurant name. The matching problem is consistent over multiple matching methods, including strict string matching, Stata's reclink, and Python's fuzzywuzzy. Relaxing the strictness of the matching programs increases the number of matches slightly but also increases the false match rate. However, the overall pass-through results are consistent across matching types, but with slightly larger magnitudes, when relying only on matched RUSA data and using the specific minimum wage increase by number of employees in NYC.

updated menu prices as customers order directly from the site. Limited service and franchise restaurants are a small portion of the restaurants in both data sets. Since limited service restaurants have been shown to have a higher level of pass-through because they employ more workers at a binding minimum wage (e.g. Aaronson, French, & MacDonald (2008); Allegretto & Reich (2015)), my estimates may be smaller than the pass-through occurring in the entire population of restaurants.

To analyze the existence of border effects, I restrict the sample to restaurants in NYC and the contiguous NJ counties. I first construct a distance matrix using Google Maps Distance Matrix Application Programming Interface. This service provides travel distance and time for a given origin and destination based on the recommended driving route. I calculate a distance matrix for each restaurant in the sample, which is comprised of driving time to all restaurants in the full Yelp sample that are on the opposite side of the border. The minimum of these driving times is then recorded for analysis as distance to the border. This provides a more accurate measure of distance than raw miles. For the border effects analysis, I include all restaurants that are within 12 minutes of the NYC-NJ border, as Iacono et al. (2008) found that 90% of Americans travel 12 minutes at maximum to go to a restaurant. Although the Hudson river separates these two areas, more than 400,000 people commute from NJ to NYC (United States Census Bureau, 2015), suggesting that the restaurants on either side of this border are in the same market. Figure 2 displays the restaurants that are included in the border effects analysis. In the Yelp data, there are 607 restaurants in NYC within 12 minutes of the border, and 395 in NJ. The restaurants in NYC that are close to the border are statistically similar to the overall NYC sample on starting price, star rating, total items, and total change in price. The NJ restaurants that are close to the border also have statistically similar characteristics to the full NJ sample on all of these measures. In the Grubhub data, there are 371 restaurants within 12 minutes of the border in NJ, and 323 in NYC. These Grubhub restaurants that are close to the border are similar to the full sample of their respective minimum wage group on starting price, total items, and total change in price.

4 Price Pass-Through

4.1 Analytical Model

My primary analysis estimates the extent to which increases in the minimum wage are passed on to consumers through prices. The baseline equation of price pass-through at the restaurant level regresses the log change in price on the log change in the minimum wage,

$$\Delta \ln p_{jkt} = \sum_{h=l}^{L} \beta_h \Delta \ln mw_{kt-h} + \gamma P\_START_j + \zeta T\_BTWN_{jkt} + \varepsilon_k + \varepsilon_m + \varepsilon_{jkt} \tag{1}$$

where p_{jkt} is the average price of items at restaurant j in minimum wage group k in observation wave t.[6] I allow for a flexible price response from restaurants by including contemporaneous and lagged changes in minimum wage. For the specifications using the Yelp data, I include two lead periods in addition to the one lag period ($l = -2, L = 1$) in order to analyze the existence of any relationship between price increase and minimum wage group before the policy implementation. Although all groups knew of the policy changes by April 2016, it is unlikely that restaurants responded to the impending wage hikes more than four months in advance. For example, Aaronson et al. (2008) found that restaurants do not respond to changes in the minimum wage more than two months ahead of implementation. Therefore, the estimates of these lead terms are a good indication of the existence of potential policy endogeneity. For the Grubhub specification, I include no lead and three lag periods ($l = 0, L = 3$). No lead period can be included since the first period of observation is in December 2016. Although there are three lags included in the Grubhub specification, these time periods encapsulate price changes over the same three month period as the one period lag in the Yelp specification.

The average price at a restaurant before the change in minimum wage is the primary means in which to characterize restaurants in the datasets. Thus, P_START_j is the average price at restaurant j in the first observation period (April 2016 for the Yelp data and December 2016 for the Grubhub data).[7] Since I collected the data using a web scrape, there was some variability in the timing of data collection for each restaurant in each wave. The variable T_BTWN_{jkt} is an integer representing the number of days between observations for a given restaurant, and ε_m is a fixed effect controlling for the month that I collected the data. Together, these two terms account for any differences in the timing of the data collection between waves as well as any seasonality. To test the extent to which other restaurant characteristics are driving the price pass-through estimates, I include X_j, a vector of RUSA variables, in some specifications. This control vector includes sales volume, number of employees, limited service status and franchise status. The key assumption in this identification strategy is that NJ is an appropriate counterfactual for NY and MA, in that the changes in minimum wage are uncorrelated with unobserved determinants of price. As discussed in Section 2, NJ

[6] Each restaurant is location specific, and p_{jkt} is the mean price in U.S dollars of all menu items at restaurant j in the balanced panel. Since less than 1% of the sample are franchise restaurants, I do not include fixed effects for restaurants in the same franchise.

[7] Although estimates for γ are significant, including P_START_j does not significantly change the coefficients of interest.

is geographically close and socioeconomically similar to both states that did increase the minimum wage. NJ also has a similar political sentiment amongst elected state congressional representatives, as the state attempted to increase their own minimum wage at the start of 2017.

4.2 Estimates

I report the results of equation (1) in Table IV. All estimates are interpreted as the percent change in price due to a 10% increase in the minimum wage over the given time period. All standard errors are clustered at the minimum wage group level.[8] The row titled "Total Pass Through" is a linear summation of the estimated coefficients in all relevant time periods. For the specifications using the Yelp data, the total pass-through estimates are linear combinations of the October '16 to January '17 and the January '17 to April '17 estimates. Since the April '16 to July '16 and July '16 to October '16 estimates are only included in the equation as a means of testing for policy endogeneity, these coefficients are not included in the total pass-through. For the specifications using the Grubhub data, the coefficients of all time periods are included in the total pass-through estimates as there are no lead terms included in the equation.

Column 1 reports estimates using the full Yelp sample of restaurants. There was significant pass-through in both the contemporaneous and lagged time periods, for a combined pass-through estimate of 0.31%. Column 2 includes the vector of control variables from the RUSA dataset.[9] These estimates are statistically similar but larger in magnitude than the estimates reported with the full sample, indicating that sales volume, number of employees and limited service status are not substantially driving the estimates. To focus analysis on restaurants that are updating menus and not posting outdates prices, column 3 restricts the full Yelp sample to only those restaurants who changed the price of at least one item throughout the course of the dataset. The total pass-through estimate for this subsample is larger at 1.07%. In all three of these specifications, the two lead period pass-through estimates are insignificant and relatively small in magnitude. This provides evidence against the presence of policy endogeneity within these minimum wage groups. The last two columns of Table IV report estimates using the Grubhub dataset. The estimated pass-through using the full Grubhbub dataset, as shown in column 4, is 0.85%. This estimate is larger than the full Yelp

[8] Since there are only five clusters, I also implemented the wild cluster bootstrap method as recommended by Cameron, Gelbach and Miller (2008). These bootstrapped standard errors are unchanged but if anything are slightly smaller by 0.005. As a result, I report the more conservative standard errors, which are clustered at the group level, throughout the paper.

[9] The sample size is smaller in column 2 than in column 1 since not all restaurants are matched to the RUSA dataset. The pass-through estimates when using the subsample of restaurants that are matched to RUSA and without including the control vector are slightly smaller than the estimates in column 2.

sample estimate, but not statistically different from the estimate using only the Yelp restaurants that updated prices. This comparison suggests that the full sample Yelp estimates may be a lower bound for the true pass-through. Column 5 reports that adding the control vector of RUSA restaurant characteristics provides a higher pass-through estimate of 1.02%.

These main pass-through estimates are consistent with findings in the previous literature (e.g. Aaronson, French, & MacDonald (2008); Allegretto & Reich (2015); Basker & Khan (2016)). These pass-through estimates are also consistent with what is predicted by the model of competitive factor markets and monopolistically competitive product markets. Assuming that firms have a constant returns to scale production function, then an increase in minimum wage will be proportionally passed on to consumers through output prices based on the minimum wage costs share of total costs. The minimum wage costs share of total costs is estimated to be between 4% and 10% in the restaurant industry (U.S. Department of Commerce, 2002; Aaronson & French, 2007). Taking these estimates as given, the model of monopolistically competitive firms and competitive factor markets then predicts that a 10% increase in the minimum wage would lead to a pass-through of 0.4% to 1.0%.

To investigate heterogeneity of price pass-through across restaurant characteristics, Table V reports the pass-through estimates by highest and lowest third of sales volume, number of employees, and star rating. All estimates are calculated using equation (1) and Yelp data. Total pass-through estimates are linear combinations of the coefficients for October ‘16 to January ‘17 and January ‘17 to April ‘17. Columns 1 and 2 compare restaurants by highest and lowest third of sales volume. Although the low sales volume estimate is larger at 0.73%, it is not significantly different from the pass-through estimate of high sales restaurants, 0.43%. Columns 3 and 4 compare restaurants by the number of employees. The pass-through estimate of 0.60% for small restaurants is significantly higher than the estimate of 0.42% for large restaurants. These results are consistent with Allegretto and Reich (2015) who found price pass-through to be larger in magnitude for restaurants with a small number of employees. Columns 5 and 6 compare restaurants by Yelp star rating in April 2016, before any minimum wage changes. The estimated price pass-through for low star restaurants, 0.28%, is higher than the estimate for high star restaurants, 0.09%, but not significantly so.

Given the unique nature of the datasets, I can also explore heterogeneity across item type. Table VI reports pass-through results at the item level using the Grubhub dataset.[10] I use the baseline specification

[10] The same patterns exist in the Yelp dataset, but item categories are not as clearly defined and so significantly more items fall into the other category. Yelp menus also do not provide a popular category.

of equation (1), except now an observation is an item. Column 1 reports pass-through estimates at the item level for all items, with a total pass-through estimate of 0.48%. This estimate is smaller than the pass-through estimates reported when aggregating at the restaurant level. Analyzing pass-through at the item level assigns more weight to restaurants with a large number of items. In the data, total number of items offered on the menu is negatively correlated with the number of items that change price at any given time. In other words, restaurants with a relatively large number of items offered on the menu change prices for a smaller proportion of these items than restaurants with a relatively small number of items. Thus the item level pass-through estimates are expected to be lower than estimates aggregated at the restaurant level. The subsequent columns of Table VI report pass-through estimates for the seven most frequent item categories.[11] The price pass-through for popular, side and sandwich items is significantly higher than the average of all items, at 0.59%, 0.67% and 0.72%, respectively. In contrast, price pass-through for entrée and drink items is significantly lower than the average of all items, both estimated at 0.38%. These estimates suggest that items such as popular and sandwich may be more inelastic than other items such as entrée and drink. These are the first estimates of differing magnitudes of pass-through by item type in the literature.

5 Quality Changes

5.1 Model

I now examine effects of a minimum wage increase on customer-perceived quality. To investigate this relationship, I use the following equation to analyze the effect of a minimum wage increase on the Yelp star rating of restaurant j in minimum wage group k at observation wave t:

$$\Delta \ln(stars_{jkt}) = \alpha + \sum_{h=l}^{L} \beta_h \Delta \ln mw_{kt-h} + \gamma P\_START_j + \varepsilon_k + \varepsilon_t + \varepsilon_{ijkt} \quad (2)$$

The variable $stars_{jkt}$ is the rounded half star rating of each establishment. As in the equation (1), I include contemporaneous and lag terms for changes in the minimum wage to allow for a flexible response. Since I use the Yelp data, I also include two lead terms ($l = -2, L = 1$) as a check for any pre-policy change relationships between minimum wage group and changes in quality. The term P_START_j, the average price at an individual restaurant in April 2016, is included as a control. The average price of items at a restaurant may provide customers with an expectation of what the level of quality should be. These ex ante ideas of

[11] The categories not reported include: appetizers, pizza, kids, breakfast, and other.

quality level could have an impact on changes in customer-perceived quality. Fixed effects for observation time period and minimum wage group are included in all specifications.[12] I assume that there are no other unobserved characteristics of restaurants that influence both the minimum wage group that a restaurant belongs to and changes in customer-perceived quality.

5.2 Estimates

The results of equation (2) are presented in Table VII. All estimates are interpreted as the percent change in star rating due to a 10% increase in minimum wage. The total percent change in star rating is a linear summation of the estimated coefficients from October '16 to January '17 and January '17 to April '17. This term can be interpreted as the "pass-through" of quality due to a 10% increase in minimum wage. The estimates from April '16 to July '16 and July '16 to October '16 are not included in the total change since these variables are only included in the equation as a test of pre-trend relationships. The first column of the table reports estimates using all Yelp restaurants that had a star rating between 2.5 and 4.5, inclusive, in each wave of data.[13] The total change in quality rating due to a 10% minimum wage increase is estimated at -0.4%.

Column 2 reports the estimated change in star rating due to a minimum wage increase for restaurants that had a 2.5 rating in April '16. The estimated relationship is more negative than the full sample at -0.9%, but imprecisely estimated. Column 3 reports the estimated relationship for restaurants that started at a 3.0 star rating. For these restaurants, a 10% increase in minimum wage is associated with a 1.9% decrease in star rating. Column 4 reports estimates for restaurants that began with a 3.5 star rating, the median in the sample. The estimated relationship for these restaurants is -1.0%. As seen in columns 5 and 6, the estimated relationship for restaurants that started at a 4.0 or 4.5 star rating is significantly positive. Restaurants starting at a 4.0 rating saw a 0.3% increase in star rating due to a 10% increase in the minimum wage, and restaurants starting at a 4.5 rating saw a 0.2% increase in star rating. Controlling for changes in price does not significantly change these estimates, suggesting that the changes in quality are not driven by customer dissatisfaction directed at price increases. These estimates are also economically significant. For

12 Using the observation period fixed effects are the same as using month fixed effects in this equation since the star ratings for each restaurant are collected in the same month for all restaurants. This is why there is no need to control for time between observations, since the time between for the star rating is uniform throughout.

13 Restaurants below a 2.5 rating and above a 4.5 rating are not analyzed as subsamples given that they are close to the lower and upper bounds of quality ratings, respectively, and so only have one direction to move. Over 90% of the restaurants with star ratings fall within this 2.5 - 4.5 range.

example, for a 3.0 star restaurant, a 10% minimum wage increase is associated with a 0.06 star decrease in rating, which is 13% of the average decrease in star rating between observations.

To gain insight into a possible mechanism of these overall quality results, I next use the percent change in the Grubhub food specific quality rating as the outcome variable in equation (2).[14] Table VIII reports the results. The estimated total percent change in food quality rating due to a 10% increase in minimum wage is -0.3% as reported in column 1. To analyze differences in food quality changes by initial firm quality, I separate all restaurants by the median food quality rating in December '16.[15] The estimated relationship between minimum wage increase and changes in food quality for restaurants that started at or below the median food quality rating is significantly estimated at -1.2%. For restaurants starting above the median, however, the relationship is estimated to be 0.34%. Similar to the overall quality results found using the Yelp data, the Grubhub food quality results suggest that firms respond differently to a minimum wage increase based on initial quality. A decrease in food quality due to a minimum wage increase for lower quality restaurants suggests that restaurants are decreasing quality in the form of lower quality ingredients or smaller portion sizes. An increase in food quality for higher rated firms suggests that a minimum wage may be working as an efficiency wage or that higher quality firms are able to substitute toward more productive workers, increasing overall output quality.

6 Border Effects

6.1 Model

To examine the existence of border effects, I restrict the sample to restaurants that are located within twelve minutes of the NYC-NJ border.[16] Figure 2 provides a closer look at the restaurants in these areas, highlighting the restaurants used in the analysis. The specification used to test the existence of border effects

[14] I also used sentiment analysis on the text of customer reviews in the Yelp data to create a measure of positive and negative service specific reviews. Restricting the sample to restaurants that had at least one positive or negative service review per quarter drastically decreased the sample sizes, with only 502 restaurants at or below the median and 729 above. This is in comparison to the 3,506 restaurants at or below the median and 2,886 above the median used in the overall Yelp star analysis. However, results are consistent in that I find that restaurants above the median significantly increase the service quality due to a minimum wage increase and restaurants at or below decrease service quality, although the latter is insignificantly measured.

[15] The results are similar when I use an aggregated quality rating comprised of the food quality, delivery quality, and accuracy ratings.

[16] The results are persistent further out from the border, but smaller in magnitude.

is

$$\Delta\ln(p_{j,Oct16-Apr17}) = \alpha_0 + \alpha_1 \mathbb{1}(NY=1) + \alpha_2 D_j + \alpha_3[D_j * \mathbb{1}(NY=1)] + \varepsilon_j, \tag{3}$$

where $\mathbb{1}(NY=1)$ is an indicator function denoting if restaurant j is located in NYC, and D_j is the driving distance in minutes to the closest restaurant on the opposite side of the border.[17] Due to the Hudson River which separates NYC and NJ, the shortest distance between two restaurants on opposite sides of the border is 8 minutes. I therefore normalize the distance for the NYC restaurants to zero as to not count this gap distance twice. In the data there are no significant relationships between distance to the border and sales volume, number of employees or limited service status. I assume that there are no other unobserved variables that are related to both the distance to the border and the change in price.

For restaurants in NYC, the equation becomes

$$\Delta\ln(p_{j,Oct16-Apr17}) = (\alpha_0+\alpha_1) + (\alpha_2+\alpha_3)D_j + \varepsilon_j.$$

The coefficient $\alpha_2+\alpha_3$ describes the relationship between distance to the border and price increase for restaurants in NYC. For a restaurant in NJ, the equation becomes

$$\Delta\ln(p_{j,Oct16-Apr17}) = (\alpha_0) + (\alpha_2)D_j + \varepsilon_j.$$

The coefficient α_2 describes the relationship between distance to the border and price increase for restaurants in NJ close to the NYC border. Figure 4 displays a binned scatter plot of the relationship between distance to the NYC-NJ border and price increase.

6.2 Estimates

I report the results of equation (3) in Table IX. Columns 1 and 2 include restaurants in the Yelp dataset. Column 1 reports the estimated relationship between price changes from October '16 to April '17 and the distance to the border for restaurants on the NYC-NJ border. The estimates show that a restaurant 10 minutes further from the border increases prices by 0.11 percentage points more than a restaurant on the border. No

[17] I selected the linear specification base on the AIC and BIC values in comparison to the quadratic specification.

significant border effects are reported for NJ restaurants. Column 2 reports this same relationship but for a price change from April '16 to October '16. This estimate is not significant, suggesting that these border effects are not always present and are driven by minimum wage changes. Column 3 reports estimates of border effects using the Grubhub dataset. The estimate suggests that restaurants in NYC 10 minutes further from the border increase prices by 0.18 percentage points more than a restaurant on the NYC-NJ border. The average change in price from October '16 to April '17 for all Yelp restaurants in NYC was 0.81%, and the average change from December '16 to April '17 for all NYC Grubhub restaurants was 1.3%. Thus the estimated border effects are relatively large in magnitude, comprising more than 10% of the total price increase seen during this time period.

7 Conclusion

In this paper, I estimate the effects of a minimum wage increase on restaurants' price and quality. I take advantage of a series of simultaneous minimum wage increases and the growing online presence of restaurants to investigate heterogeneity in price pass-through across restaurant characteristics and item type, changes in customer-perceived quality, and the existence of border effects. I find that prices increase between 0.3 to 1.1% in response to a 10% increase in minimum wage, results that are consistent with previous literature. Since the data I use in this study are primarily non-chain and full service restaurants, these results are not being driven by large franchises and limited service establishments. The price pass-through estimates differ across restaurant characteristics, with the estimates significantly higher for smaller restaurants. The magnitude of the price pass-through also varies at the item level, where items in categories such as popular, side and sandwich show a significantly higher pass-through level, but items in categories such as drinks and entrées show significantly lower levels of pass-through. This suggests that different item types have different elasticities, and that studies which examine prices of only a few menu items may significantly under or over estimate price pass-through.

I find a bimodal effect of an increase in the minimum wage on restaurant quality. Restaurants that were rated at the median or below prior to the minimum wage increase saw a significant decrease in the quality rating given to them by consumers after an increase in minimum wage. Restaurants that started at ratings above the median saw a positive effect on their consumer ratings due to the increase in minimum wage. The results are consistent over two different measures of customer-perceived quality. These results suggest that lower quality firms may decrease output quality in response to a minimum wage increase. However, a minimum wage may act as an efficiency wage in higher quality restaurants, or higher quality restaurants may be able to substitute toward higher quality workers. Lastly, I examine the extent to which a restaurant's proximity to a minimum wage policy border affects the level of price pass-through. I find that restaurants close to a minimum wage policy border increase prices by significantly less than restaurants further from the border. These border effect estimates have significant economic implications, suggesting that a local minimum wage increase may impede the ability of restaurants on a minimum wage policy border to fully pass-through prices to consumers. Overall, these data have provided the opportunity to look further into the effects of a minimum wage increase on restaurants and have brought about new areas of exploration for further research.

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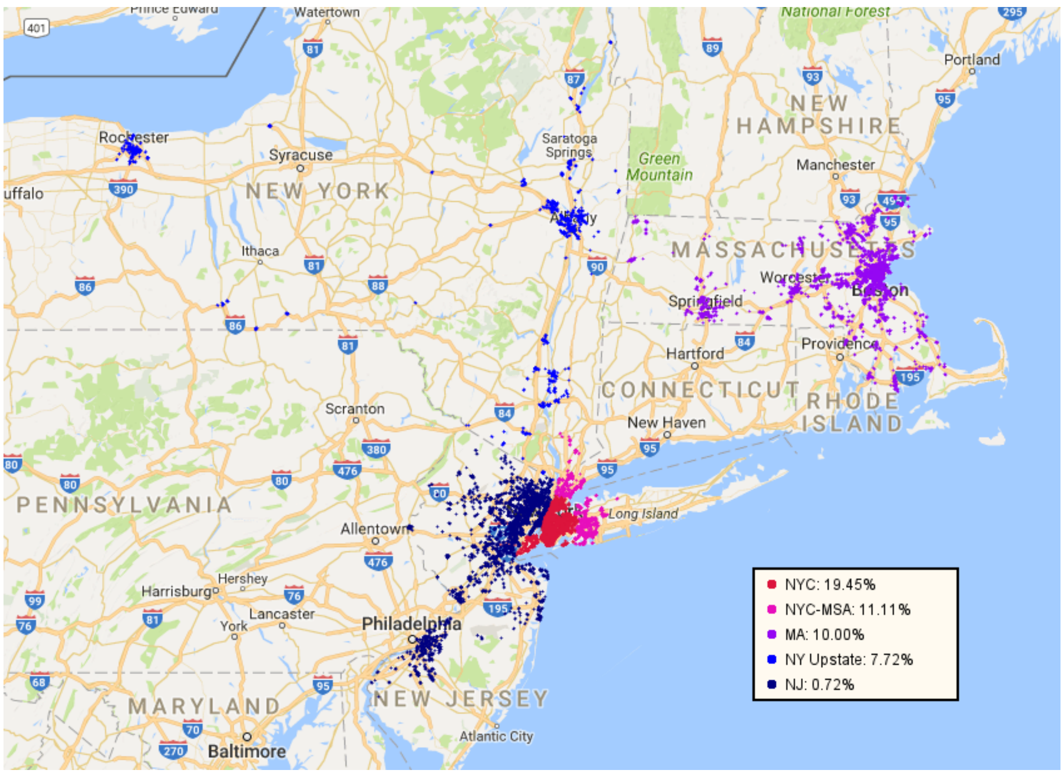
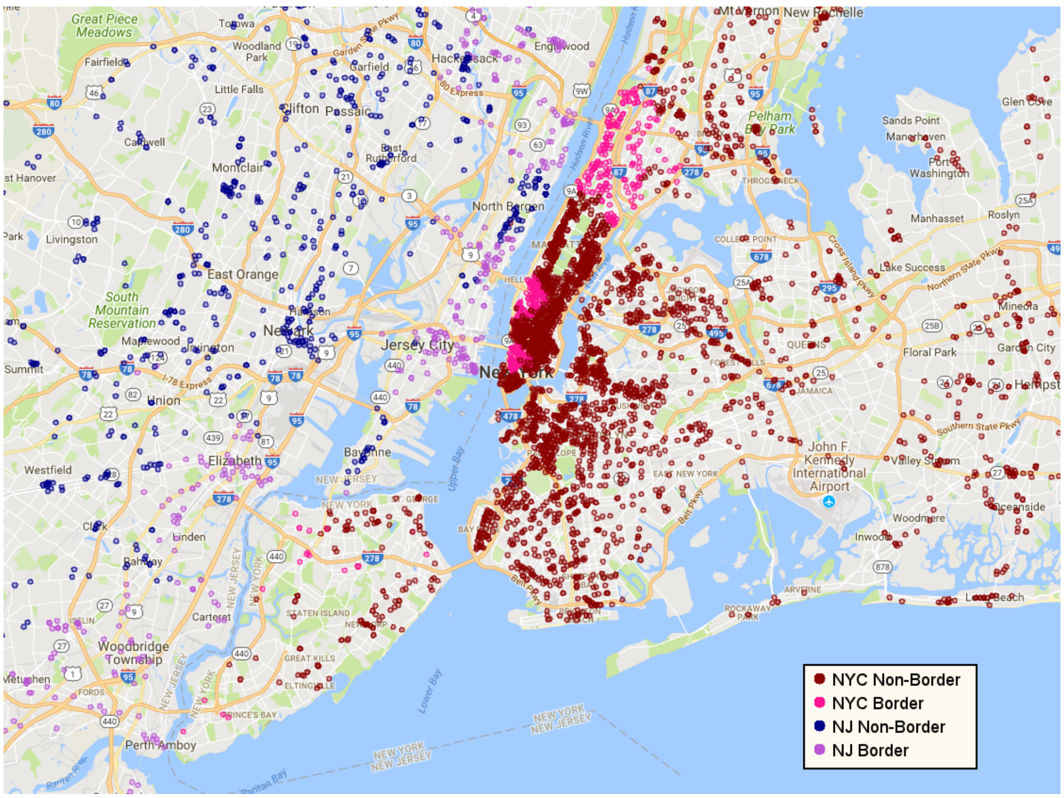
Figures

Figure I: Sample of Yelp Restaurants



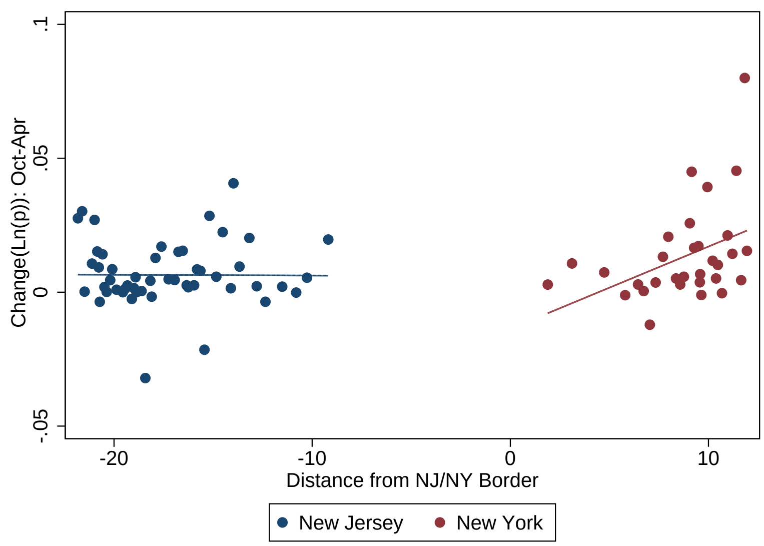
Notes: Each data point represents a restaurant in the Yelp dataset. Samples are color coded by percent increase in minimum wage on January 1, 2017. NYC saw the highest increase in minimum wage at 19.45%. NYC-MSA, which includes Nassau, Suffolk, and Westchester counties, saw the second highest increase at 11.11%. The minimum wage increased in MA by 10.00%, in Upstate NY by 7.72% and in NJ by 0.72%.

Figure II: Geographic Location of Restuarants Used in Border Effects Analysis



Notes: Each data point represents a restaurant in the Yelp dataset in NJ and NYC. Samples are color coded by the magnitude of the increase in minimum wage on January 1, 2017. The highlighted restaurants in each group represent the restaurants that are within twelve minutes from the border and are used in the border effects analysis.

Figure III: Border Effects: Price Pass Through by Distance to NYC/NJ Border



Notes: The figure shows the relationship between the change in price from October 2016 to April 2017 and the distance to the NYC-NJ border. Restaurants are binned into 80 quantiles. There is a gap between the NYC and NJ restaurants due to the Hudson River which separates the two states. Distance is measured in driving minutes to the nearest restaurant on the opposite side of the border.

Tables

Table I: Minimum Wage Policy Changes

	Regular Minimum Wage			Tipped Minimum Wage		
Area	2016	2017	%Δ	2016	2017	%Δ
NYC & Lg	\$9.00	\$11.00	22.22%	\$7.50	\$7.50	0.00%
NYC & Sm	\$9.00	\$10.50	16.67 %	\$7.50	\$7.50	0.00%
NYC MSA	\$9.00	\$10.00	11.11%	\$7.50	\$7.50	0.00%
NY Upstate	\$9.00	\$9.70	7.78%	\$7.50	\$7.50	0.00%
New Jersey	\$8.38	\$8.44	0.72%	\$2.13	\$2.30	0.00%
Massachusetts	\$10.00	\$11.00	10.00%	\$3.00	\$3.75	25.00%

Notes: The regular and tipped minimum wage changes from 2016 to 2017 are reported by group. The first two rows show the minimum wage changes for restaurants in NYC. A small restaurant is defined as having 10 employees or less, and a large restaurant is defined by more than 10 employees. For the main analysis I use the average of the two minimum wage changes, 19.45%, for both small and large restaurants in NYC. The NYC MSA group consists of restaurants in the three contiguous counties to NYC: Nassau, Suffolk, and Westchester. NY Upstate encapsulates restaurants in all other areas of the state. NJ and MA minimum wage laws are consistent throughout each state.

Table II: Yelp Restaurant Summary Statistics by Minimum Wage Group

	(1) NYC	(2) NYC MSA	(3) MA	(4) NY Upstate	(5) NJ	(6) F Test Sig.
Min Wage Increase	0.194	0.111	0.100	0.078	0.007	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Starting Price (Apr16)	9.781	10.703	9.891	9.622	9.869	0.044
	(0.108)	(0.268)	(0.136)	(0.375)	(0.183)	
Number of Items	71.679	81.590	68.008	58.653	75.188	0.000
	(1.113)	(2.794)	(1.503)	(2.459)	(1.686)	
Change Price (Apr16-Oct16)	0.005	0.002	0.003	0.003	0.005	0.428
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	
Change Price (Oct16-Apr17)	0.008	0.007	0.005	0.001	0.004	0.091
	(0.001)	(0.004)	(0.001)	(0.001)	(0.002)	
Difference in Change in Price	0.003	0.005	0.002	-0.002	-0.000	0.405
	(0.001)	(0.005)	(0.002)	(0.002)	(0.002)	
Increase	0.145	0.089	0.115	0.040	0.085	0.000
	(0.005)	(0.012)	(0.008)	(0.009)	(0.007)	
Decrease	0.041	0.025	0.028	0.015	0.032	0.004
	(0.003)	(0.006)	(0.004)	(0.005)	(0.004)	
Price Change ‖ Increase	0.083	0.108	0.064	0.048	0.087	0.201
	(0.002)	(0.011)	(0.003)	(0.003)	(0.005)	
Price Change ‖ Decrease	-0.100	-0.089	-0.097	-0.048	-0.095	0.950
	(0.003)	(0.006)	(0.002)	(0.003)	(0.003)	
Sales (100k)	8.489	7.597	9.233	5.019	5.631	0.000
	(0.219)	(1.524)	(0.471)	(0.263)	(0.226)	
Employees	10.836	10.227	14.603	10.222	9.267	0.000
	(0.237)	(0.858)	(0.604)	(0.519)	(0.360)	
Limited Service	0.042	0.072	0.019	0.069	0.043	0.000
	(0.003)	(0.011)	(0.003)	(0.011)	(0.005)	
Franchise	0.001	0.006	0.016	0.000	0.010	0.000
	(0.000)	(0.003)	(0.003)	(0.000)	(0.002)	
N	4242	595	1658	519	1793	

Notes: The means and standard errors of the primary dataset, Yelp, are reported. Each of the first five columns contains the restaurants that fall into a specific minimum wage group. All data is balanced at the item level across time periods and aggregated at the restaurant level. Price is measured in U.S. dollars. The fourth and fifth rows report mean change in natural log of the price, which is approximately the percentage change. The sixth row reports the difference in the previous two rows, showing the change in trends between pre and post-policy implementation. The rows titled "Increase" and "Decrease" report the percentage of restaurants that increased or decreased price between Oct '16 and Apr '17. The conditional price changes are calculated from Oct '16 to Apr '17. Column 6 displays the p-value of the multiple means test using the respective variable and all five groups.

Table III: Grubhub Restaurant Summary Statistics by Minimum Wage Group

	(1) NYC	(2) NYC MSA	(3) MA	(4) NY Upstate	(5) NJ	(6) F Test Sig.
Min Wage Increase	0.194	0.111	0.100	0.078	0.007	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Starting Price (Dec16)	9.356	9.759	9.346	8.640	8.949	0.001
	(0.087)	(0.148)	(0.142)	(0.147)	(0.104)	
Number of Items	107.790	133.704	117.472	105.053	126.917	0.000
	(1.386)	(3.671)	(2.509)	(3.954)	(2.395)	
Change Price (Dec16-Apr17)	0.013	0.008	0.009	0.013	0.006	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	
Increase	0.374	0.326	0.294	0.349	0.292	0.000
	(0.007)	(0.020)	(0.015)	(0.025)	(0.013)	
Decrease	0.066	0.060	0.053	0.047	0.073	0.242
	(0.004)	(0.010)	(0.008)	(0.011)	(0.007)	
Price Change || Increase	0.040	0.027	0.035	0.037	0.029	0.000
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	
Price Change || Decrease	-0.025	-0.019	-0.030	-0.011	-0.026	0.896
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	
Sales (100k)	8.643	3.218	4.976	4.684	2.987	0.000
	(0.654)	(0.171)	(0.262)	(0.336)	(0.083)	
Employees	9.916	5.650	7.996	9.582	5.130	0.000
	(0.290)	(0.294)	(0.416)	(0.714)	(0.142)	
Limited Service	0.042	0.070	0.029	0.067	0.065	0.013
	(0.003)	(0.011)	(0.006)	(0.013)	(0.007)	
Franchise	0.004	0.007	0.011	0.021	0.000	0.006
	(0.001)	(0.004)	(0.004)	(0.008)	(0.000)	
N	4172	565	866	358	1320	

Notes: The means and standard errors of the secondary dataset, Grubhub, are reported. Each of the first five columns contains the restaurants that fall into a specific minimum wage group. All data is balanced at the item level across time periods and aggregated at the restaurant level. Price is measured in U.S. dollars. The fourth row reports mean change in natural log of the price, which is approximately the percentage change. The rows titled "Increase" and "Decrease" report the percentage of restaurants that increased or decreased price between Dec '16 and Apr '17. The conditional price changes calculated from Dec '16 to Apr '17. Column 6 displays the p-value of the multiple means test using the respective variable and all five groups.

Table IV: Main Price Pass-Through Results

	Yelp			Grubhub	
	(1)	(2)	(3)	(4)	(5)
	Baseline	Controls	Change	Baseline	Controls
$Apr16 - Jul16$	-0.019	0.053	-0.149		
	(0.062)	(0.114)	(0.374)		
$Jul16 - Oct16$	0.069	0.063	0.262		
	(0.080)	(0.120)	(0.409)		
$Oct16 - Jan17$	0.163	0.208	0.604		
	(0.056)	(0.083)	(0.317)		
$Jan17 - Apr17$	0.150	0.180	0.464		
	(0.060)	(0.096)	(0.353)		
$Dec16 - Jan17$				0.254	0.272
				(0.002)	(0.010)
$Jan17 - Feb17$				0.233	0.331
				(0.016)	(0.040)
$Feb17 - Mar17$				0.188	0.246
				(0.021)	(0.015)
$Mar17 - Apr17$				0.171	0.165
				(0.008)	(0.020)
Total Pass Through	0.313	0.388	1.068	0.845	1.015^{+}
	(0.115)	(0.171)	(0.669)	(0.031)	(0.083)
N	8805	5257	2099	7280	3230
NxT	35220	21028	8396	29120	12920

+ statistically different than respective baseline estimate

Notes: The outcome variable for all columns is the log change in price at the restaurant level. All standard errors are clustered at the minimum wage group level. Each row represents the amount of pass-through occurring in the lag(s), lead(s), and contemporaneous time periods of the minimum wage changes. For the specifications using the Yelp data, (1)-(3), the total pass-through estimates are linear combinations of the October '16 to January '17 and the January '17 to April '17 estimates. For the specifications using the Grubhub data, (4)-(5), all time periods are included in the total pass-through estimates. The first column includes the full Yelp sample. The second column includes the vector of controls from the RUSA dataset, comprised of sales volume, number of employees and limited service status. The third column includes only restaurants that changed at least one item over the time period of the dataset. Column 4 reports price pass-through estimates using the full Grubhub sample. Column 5 includes the vector of RUSA control variables.

Table V: Price Pass Through By Restaurant Characteristics

	(1) Low Sales	(2) High Sales	(3) Low Emps	(4) High Emps	(5) Low Stars	(6) High Stars
$Apr16-Jul16$	0.288	0.182	0.249	0.122	-0.076	-0.003
	(0.145)	(0.271)	(0.147)	(0.260)	(0.142)	(0.182)
$Jul16-Oct16$	0.249	-0.073	0.286	0.019	-0.131	0.028
	(0.182)	(0.204)	(0.140)	(0.245)	(0.126)	(0.073)
$Oct16-Jan17$	0.260	0.096	0.364	0.032	0.170	0.033
	(0.126)	(0.121)	(0.119)	(0.155)	(0.064)	(0.064)
$Jan16-Apr17$	0.468	0.334	0.238	0.386	0.097	0.056
	(0.122)	(0.142)	(0.132)	(0.176)	(0.130)	(0.094)
Total Pass Through	0.728	0.43	0.602^{+}	0.418^{+}	0.267	0.089
	(0.244)	(0.262)	(0.231)	(0.331)	(0.19)	(0.156)
N	1556	1723	2142	1894	2020	2995
NxT	6224	6892	8568	7576	8080	11980

+ statistically different than comparison group

Notes: The reported estimates compare price pass-through of restaurants in the lowest and highest third based on sales, employees, and number of stars in April 2016 using the Yelp dataset. The outcome variable for all columns is the log change in price at the restaurant level. All standard errors are clustered at the minimum wage group level. The total pass-through estimates are linear combinations of the October '16 to January '17 and the January '17 to April '17 estimates. The cutoff values for sales are 204 and 598 thousand. The cutoff values for employees are 4 and 10, and the cutoff values for stars are 3 and 4.

Table VI: Price Pass Through By Item Type

	(1) All	(2) Popular	(3) Side	(4) Sandwich	(5) Soup/Salad	(6) Entre	(7) Dessert	(8) Drink
$Dec16-Jan17$	0.155	0.193	0.169	0.224	0.174	0.117	0.114	0.146
	(0.004)	(0.002)	(0.008)	(0.004)	(0.002)	(0.002)	(0.009)	(0.005)
$Jan17-Feb17$	0.142	0.238	0.163	0.244	0.132	0.121	0.078	0.152
	(0.013)	(0.007)	(0.054)	(0.008)	(0.008)	(0.007)	(0.024)	(0.027)
$Feb17-Mar17$	0.126	0.072	0.208	0.180	0.109	0.087	0.141	0.067
	(0.010)	(0.015)	(0.029)	(0.005)	(0.009)	(0.009)	(0.021)	(0.023)
$Mar17-Apr17$	0.060	0.084	0.115	0.070	0.099	0.050	0.041	0.015
	(0.012)	(0.010)	(0.028)	(0.038)	(0.015)	(0.015)	(0.024)	(0.014)
Total Pass Through	0.483	0.587^{+}	0.656^{+}	0.718^{+}	0.514	0.375^{+}	0.373	0.379^{+}
	(0.032)	(0.023)	(0.104)	(0.045)	(0.022)	(0.026)	(0.076)	(0.054)
N	831763	47295	107172	105265	46692	150035	18453	65112
NxT	3327052	189180	428688	421060	186768	600140	73812	260448

+ statistically different than column (1)

Notes: The outcome variable for all columns is the log change in price at the item level using the Grubhub dataset. All standard errors are clustered at the minimum wage group level. All time periods are included in the total pass-through estimates. The item categories listed above are mutually exclusive but not exhaustive. The additional food categories not listed include; appetizer, kids, pizza, and other.

Table VII: Overall Yelp Quality Changes by Initial Star Rating

	(1) All	(2) 2.5	(3) 3.0	(4) 3.5	(5) 4.0	(6) 4.5
$Apr16 - Jul16$	0.035	1.138	0.625	0.068	-1.047	-0.627
	(0.213)	(1.201)	(0.697)	(0.187)	(0.312)	(0.456)
$Jul16 - Oct16$	-0.046	-0.321	-0.305	0.109	0.198	-0.792
	(0.071)	(0.292)	(0.400)	(0.211)	(0.296)	(0.413)
$Oct16 - Jan17$	0.049	0.255	-1.341	-0.268	0.500	0.470
	(0.036)	(1.068)	(0.178)	(0.076)	(0.090)	(0.275)
$Jan17 - Apr17$	-0.416	-1.158	-0.546	-0.728	-0.252	-0.255
	(0.167)	(0.609)	(0.670)	(0.197)	(0.080)	(0.175)
Total % Change Stars	-0.368	-0.903	-1.887	-0.996	0.248	0.215
	(0.138)	(1.667)	(0.813)	(0.161)	(0.123)	(0.164)
N	6392	625	1080	1801	1904	982
NxT	25568	2500	4320	7204	7616	3928

Notes: The outcome variable for all columns is the log change in Yelp star rating. All standard errors are clustered at the minimum wage group level. The total percent change in stars estimates are linear combinations of the October '16 to January '17 and the January '17 to April '17 estimates. The initial star ratings are the rounded Yelp star ratings in April '16. Restaurants below a 2.5 rating and above a 4.5 rating are not analyzed as subsamples given that they are close to the lower and upper bounds, respectively, and so only have one direction to move.

Table VIII: Grubhub Food Specific Quality Changes by Initial Quality Rating

	(1) All	(2) <= Median	(3) > Median
$Dec16 - Jan17$	-0.069	-0.349	0.156
	(0.061)	(0.181)	(0.052)
$Jan17 - Feb17$	-0.023	-0.210	0.136
	(0.102)	(0.169)	(0.049)
$Feb17 - Mar17$	-0.171	-0.317	-0.018
	(0.045)	(0.051)	(0.037)
$Mar17 - Apr17$	-0.054	-0.176	0.048
	(0.019)	(0.056)	(0.066)
Total % Change Rating	-0.316	-1.215	0.344
	(0.000)	(0.003)	(0.004)
N	7281	3979	3302
NxT	29124	15916	13208

Notes: The outcome variable for all columns is the log change in Grubhub food quality rating. The food specific quality rating is on a 1 to 100 scale and represents the proportion of customers that reported that "the food was good" after receiving their order. All standard errors are clustered at the minimum wage group level. The total percent change in rating estimates are linear combinations of all rows. The median food quality rating is 89.

Table IX: Border Effects

Source	Yelp		Grubhub
	(1)	(2)	(3)
Time Frame	Oct16-Apr17	Apr16-Oct16	Dec16-Apr17
$\mathbb{1}(NY)$ (α_1)	0.0064	-0.0064	-0.0102
	(0.0152)	(0.0116)	(0.0124)
Distance (α_2)	-0.0009	0.0000	-0.0000
	(0.0008)	(0.0006)	(0.0006)
Distance * $\mathbb{1}(NY)$ (α_3)	0.0020	0.0007	0.0019
	(0.0011)	(0.0009)	(0.0009)
Constant (α_0)	-0.0069	0.0041	0.0059
	(0.0134)	(0.0102)	(0.0101)
$\alpha_2 + \alpha_3$	0.0011	0.0007	0.0018
	(0.0008)	(0.0006)	(0.0007)
N	1002	1002	694

Notes: The outcome variable is the percentage point change in price due to a 10 minute change in the distance of a restaurant to the border. The first column includes restaurants in the Yelp dataset within twelve minutes of the NYC - NJ border between October 2016 and April 2017. Column 2 includes these same restaurants but using the change in price from July 2016 to October 2016 as the outcome. Column 3 reports effects on the NYC-NJ border using the Grubhub dataset.

A Appendix

A.1 Data Collection

The webscrape for the Yelp data collection was originally written to collect data for a different project, funded under the National Institute of Diabetes and Digestive And Kidney Diseases of the National Institutes of Health under Award Number R01DK107686. This paper analyzes the effect of the calorie posting aspect of the Affordable Care Act (Frisvold, Courtemanche, and Price, 2017). The specific aim of that project is to determine whether and why the Affordable Care Act (ACA) menu labeling requirement for restaurants impacts obesity by examining changes in consumer behavior and restaurant menus. The geographical areas of interest for this calorie posting project were created based on counties in the U.S. which had already enacted a calorie posting law for restaurants prior to the enactment of the ACA. These areas which had already enacted a calorie posting law were defined as the control groups, and the surrounding areas which had not yet enacted a calorie posting law and were affected by the ACA requirement were defined as the treatment groups. The control groups included New York City, NY, Philadelphia County, PA, King County, WA, Albany and Schenectady Counties, NY, Montgomery County, MD, and Vermont. The treatment groups included New York City MSA, Philadelphia MSA, Seattle MSA, Washington, DC MSA, Albany, NY MSA and Connecticut, Maine, Massachusetts, New Hampshire, and Rhode Island. The list of areas for data collection was thus based on obtaining a representative sample from these treatment and control groups.

I began collecting Yelp data in April, 2016, and continued data collection quarterly thereafter. Data collection began on the 15th of the first month of each quarter. The first two waves of the Yelp scrape took approximately two months for each round, but after improving the program, the subsequent scrapes took approximately two weeks for each round. This is why there is substantial variation in the time between observations for the Yelp restaurants. After three rounds of Yelp data collection, it became apparent that restaurants may not consistently post updated menu prices. To examine this potential concern, I began menu data collection using a second source, Grubhub, in December 2016. Figure A4 depicts the timeline of the data collection for both sources and the minimum wage policies. The webscrape for Yelp and Grubhub work in a similar manner. For both sources, the scrapes iterate through each area of interest, creating a list of the web page links for all restaurants. The same order of areas is used in each wave of data collection. The scrapes then randomize these restaurants and iterate through each location saving the home page and menu page for each restaurant.

After data collection is complete, I use a parsing program to manipulate the restaurant menu data into a usable format. As noted in the paper, for restaurants in the Yelp dataset, only restaurants with a uniform Yelp menu are parsed for analysis. For the round of data collection in April, 2016, the other externally formatted Yelp menus were hand entered to examine restaurant characteristics. These externally formatted menus include PDF menus and other non-Yelp HTML menus. Table A1 reports these results, comparing restaurant characteristics from the Yelp formatted menus and the externally formatted menus in April 2016. These restaurants are statistically similar on average price, percent of limited service restaurants, and percent of franchise restaurants. The external menus have more menu items, higher star ratings, lower sales volume and a smaller number of employees.

A.2 Additional Measure of Quality Changes

As reported in section 5 of the paper, I find significant changes in customer-perceived quality of restaurants due to an increase in minimum wage. Table A2 reports changes in Yelp star rating by initial quality using equation (2) but including the log change in price at each time period. The overall quality effects are similar to the results reported in Table 7. Restaurants rated at 4.0 stars prior to the minimum wage increase, however, saw an overall decrease in quality rating when controlling for changes in price, although this is imprecisely measured. Changes in price are more strongly related to changes in quality ratings for lower quality restaurants than for high quality restaurants. This suggests that price may play a larger role in customer-perceived quality for lower quality restaurants.

As another measure of quality, I performed sentiment analysis on the text of customer reviews, identifying positive and negative reviews that are specifically about service quality. I use Python's Natural Language Toolkit for all sentiment analysis. My program first identifies sentences where the subject is a service related entity (waiter, staff, hostess, etc.). Then based on a list of over 100 positive and negative adjectives that I provide to the program (helpful, nice, attentive, rude, careless, etc), classifies the sentence based on the service related adjective and adverb. I perform this sentiment analysis on all reviews for each restaurant, creating variables that identify the number of positive reviews on service and the number of negative reviews on service for each restaurant within each quarter between data collection waves. The majority of customer reviews contain general statements about a restaurant that are not specific to service quality, and therefore are not included in this measure. Restricting the sample to restaurants that had at least one positive or negative service review per quarter drastically decreased the sample sizes, with only 502 restaurants at or below the median and 729 above. This is in comparison to the 3,506 restaurants at or below the median and 2,886 above the median used in the overall Yelp star analysis. These results are shown in Table A3. The estimates are consistent with the overall Yelp quality results and the Grubhub food specific quality results, as discussed in section 5, in that I find that restaurants above the median increase the service quality and restaurants at or below the median decrease service quality after a minimum wage increase.

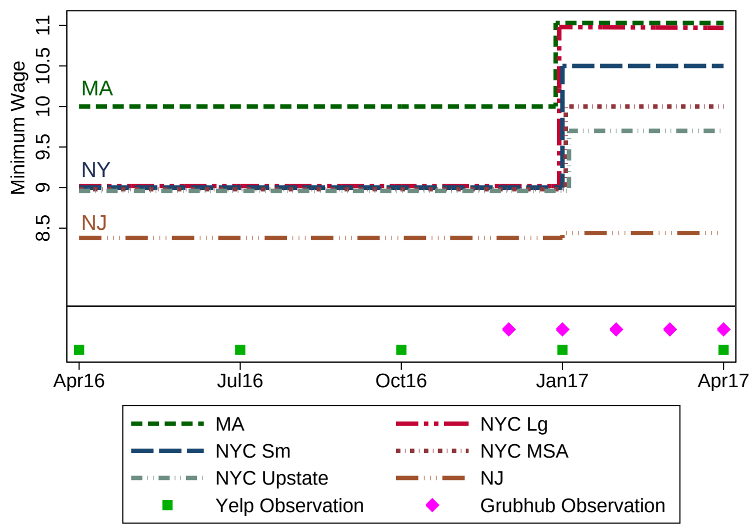
A.3 Additional Non-Price Outcomes

In addition to price and quality, there are two other variables of interest in the dataset that can be utilized as outcome variables. The first variable is the total number of menu items at each point in time. This variable is of interest since I use a balanced panel in the main results. Columns 1 and 3 in Table A4 report changes in the total number of items on the menu over time as an outcome variable using equation (2) for Yelp and Grubhub restaurants. Total percent change is a linear combination of the relevant time periods, and can be interpreted as the percent change in items offered on a menu due to a 10% increase in minimum wage. Although the results from Yelp show a positive relationship between minimum wage increase and number of items offered on the menu, the lead period coefficients are similar in magnitude and precision to the contemporaneous and lag period. Thus it is unlikely that this estimated relationship is driven by minimum wage changes. In addition, the estimated relationship is less than a quarter of an item, which suggests that any changes to the number of menu items offered is not driving the pass-through estimates.

As shown in column 3, the relationship between minimum wage increase and total number of menu items is negative in the Grubhub data. Since there are no pre-policy implementation estimates with which to compare these and the relationship between minimum wage increase and number of items is opposite of what is seen in the Yelp data, it is unclear what the true relationship is. Similar to the Yelp estimate, however, this estimate translates to less than a one-half item change due to an increase in minimum wage. Between the two datasets, no clear relationship can be concluded between the number of menu items and changes in the minimum wage.

The second additional variable is hours of operation. Each dataset provides the total number of hours of operation per week for the majority of the restaurants. Columns 2 and 4 report changes in the total number of hours open per week due to a minimum wage increase for the restaurants in both datasets using equation (2). Total percent change is a linear combination of the relevant time periods, and can be interpreted as the percent change in hours open per week due to a 10% increase in minimum wage. Although the estimates are slightly negative, this relationship is estimated as zero using both datasets.

Figure A1: Data Collection and Minimum Wage Policy Timeline



<u>Notes:</u> Minimum wage is measured in U.S. dollars. All policy changes went into effect January 1, 2017. The plots of Yelp and Grubhub observations represent the month in which each round of data collection began. Data collection for both sources began on the 15th of each given month. Yelp data was collected in April '16, July '16, October '16, January '17, and April '17. Grubhub data was collected in December '16, January '17, February '17, March '17 and April '17. Minimum wage groups and policies are defined in detail in Section 2 of the paper.

Table A1: Yelp Formatted - Externally Formatted Menu Comparison

	(1) Yelp Menus	(2) External Menus	(3) F Test Sig.
Price	10.224	10.234	0.957
	(0.067)	(0.127)	
Number of Items	85.472	103.821	0.000
	(0.545)	(1.911)	
Stars	3.552	3.712	0.000
	(0.004)	(0.011)	
Limited Service	0.055	0.060	0.372
	(0.001)	(0.004)	
Franchise	0.020	0.019	0.835
	(0.001)	(0.002)	
Sales (100k)	905.036	653.031	0.012
	(22.244)	(21.426)	
Employees	12.845	10.524	0.002
	(0.163)	(0.256)	
N	29559	3657	

Notes: The means and standard errors of all baseline characteristics are reported. Price, stars and total items are calculated using the online menu data. Limited service, franchise, sales volume and number of employees are calculated using the RUSA matched restaurants. All restaurants were collected in the April 2016 wave. Column 3 reports the p-values for the means test for each variable.

Table A2: Changes in Overall Yelp Quality Net of Price Changes

	(1) All	(2) 2.5	(3) 3.0	(4) 3.5	(5) 4.0	(6) 4.5
$Apr16 - Jul16$	-0.313	1.154	0.635	0.047	-1.308	-0.615
	(0.204)	(1.206)	(0.698)	(0.191)	(0.519)	(0.461)
$Jul16 - Oct16$	-0.163	-0.325	-0.305	0.089	-0.012	-0.775
	(0.086)	(0.282)	(0.401)	(0.209)	(0.332)	(0.410)
$Oct16 - Jan17$	-0.138	0.250	-1.348	-0.278	0.181	0.473
	(0.169)	(1.082)	(0.179)	(0.071)	(0.291)	(0.277)
$Jan17 - Apr17$	-0.527	-1.105	-0.548	-0.738	-0.386	-0.252
	(0.200)	(0.590)	(0.672)	(0.215)	(0.175)	(0.174)
Change Price	-0.034	-0.105	0.037	-0.032	-0.003	-0.033
	(0.018)	(0.049)	(0.024)	(0.031)	(0.056)	(0.032)
Total % Change Stars	-0.665	-0.856	-1.895	-1.016	-0.206	0.22
	(0.079)	(1.666)	(0.819)	(0.188)	(0.341)	(0.168)
N	6390	625	1080	1800	1903	982
NxT	25560	2500	4320	7200	7612	3928

Notes: The outcome variable for all columns is the log change in Yelp star rating. All standard errors are clustered at the minimum wage group level. The total percent change in stars estimates are linear combinations of the October '16 to January '17 and the January '17 to April '17 estimates. The initial star ratings are the rounded Yelp star ratings in April '16. Restaurants below a 2.5 rating and above a 4.5 rating are not analyzed as subsamples given that they are close to the lower and upper bounds, respectively, and so only have one direction to move.

Table A3: Changes in Yelp Service Specific Quality

	(1) All	(2) $2.5-3.0$	(3) 3.5	(4) $4.0-4.5$
$Apr16-Jul16$	-1.956	1.203	-1.828	1.109
	(0.951)	(1.852)	(1.066)	(3.860)
$Jul16-Oct16$	-0.433	3.095	-3.053	-0.716
	(0.996)	(3.507)	(2.524)	(0.892)
$Oct16-Jan17$	1.972	-1.447	8.933	-0.370
	(0.953)	(4.766)	(3.046)	(0.151)
$Jan17-Apr17$	-1.165	-0.255	-9.703	2.221
	(0.555)	(1.899)	(2.976)	(1.146)
Total Percentage Point Change	0.808	-1.702	-0.77	1.851
	(0.845)	(3.157)	(5.414)	(1.227)
N	1256	202	300	729
NxT	5024	808	1200	2916

Notes: All estimates are percentage point change in the proportion of positive Yelp service specific reviews. All standard errors are clustered at the minimum wage group level. Total percentage point change is a linear combination of the Oct '16 to Jan '17 and Jan '17 to Apr '17 estimates. Below the median and above the median restaurants are grouped together due to the small sample sizes

Table A4: Changes in Other Non-Price Outcomes

	Yelp		Grubhub	
	(1)	(2)	(3)	(4)
	Total Items	Hours Open	Total Items	Hours Open
$Apr16-Jul16$	0.158	-0.003		
	(0.061)	(0.006)		
$Jul16-Oct16$	0.230	-0.032		
	(0.040)	(0.020)		
$Oct16-Jan17$	0.142	0.000		
	(0.010)	(0.004)		
$Jan17-Apr17$	0.172	-0.000		
	(0.021)	(0.012)		
$Dec16-Jan17$			-0.286	-0.007
			(0.017)	(0.003)
$Jan17-Feb17$			-0.143	-0.001
			(0.055)	(0.013)
$Feb17-Mar17$			-0.115	-0.007
			(0.050)	(0.013)
$Mar17-Apr17$			-0.086	0.014
			(0.109)	(0.008)
Total % Change	0.315	0.000	-0.63	-0.001
	(0.029)	(0.012)	(0.199)	(0.033)
N	8807	69201	7281	6709
NxT	35228	27684	29124	26836

Notes: The outcome variable for all columns is the log change in the given outcome at the restaurant level. All standard errors are clustered at the minimum wage group level. Columns 1 and 2 use the Yelp data and total percent change is a linear combination of the Oct ‘16 to Jan ‘17 and Jan ‘17 to Apr ‘17 estimates. Columns 3 and 4 use the Grubhub data and total percent change is a linear combination of all coefficients.